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Optimization of Cutting Temperature During Turning Process to Enhance the Surface Quality Using a Hybrid Artificial Intelligence

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Abstract

Higher temperatures during turning adversely affect the cutting tool owing to thermal softening. The heightened material dispersion compromises the quality of the machined component. This research encompasses a study that experimentally examines and statistically evaluates the impact of various cutting settings on the turning performance of AISI 1045 steel. A statistical method such as analysis of variance (ANOVA) and full factorial design were used to accomplish this study. Furthermore, this paper presents the results of a series of experiments that used a hybrid artificial neural network (ANN) and genetic algorithms (GA) to optimize the cutting temperature to improve the surface quality. The results revealed that the machined surface undergoes significant tool type, cutting speed, feed rate, and depth of cut. A typical carbide insert tool, cutting speed of 80 m/min, a depth of cut of 0.5 mm, and a feed rate of 0.045 mm/rev were employed in the experiments to achieve a minimum cutting temperature of 412.9 °C. Utilizing a hybrid ANN-GA with the same values of parameters yields a cutting temperature of 436.7 °C. Consequently, ANN-GA has improved the cutting temperature and is more effective in attaining the desired result. Therefore, the cutting temperature of hybrid algorithms has been enhanced, rendering them more efficient.

Keywords
Surface quality, artificial neural network, genetic algorithms, optimization, and cutting temperature,

1. Introduction
Increased temperature during machining adversely affects tool performance and longevity, as thermal softening results in excessive tool wear, thereby reducing tool lifespan. Additionally, heightened material diffusion compromises surface integrity and changes the function of the machined component (Dhar and Kamruzzaman 2007; Nouari et al. 2003; Dosbaeva et al. 2015; Shalaby and Veldhuis 2019). Moreover, Machining at higher temperatures affects the formation of chips. Ribbon chips and snarl chips are also possible outcomes of this (Klocke and Eisenblaetter 1997). Given that temperature significantly influences tool wear, surface quality, and subsurface integrity in machining, precise monitoring of temperature fields in this process yields several advantages. Accurate microscale monitoring of thermal fields may enhance tool designs, materials, and coatings, therefore minimizing temperatures and reducing wear in machining (Davies, Cooke, and Larsen 2005). The high cutting temperature in the cutting zone leads to the cutting tools failing too soon, which in turn leads to inaccurate dimensions, making it very difficult to achieve these qualities (Magalhães et al. 2022).

Consequently, temperature monitoring and prediction have been the subject of research for several decades. The tool-chip interface thermocouple was initially investigated by (Herbert 1926), (Trigger 1948), (Stephenson 1993), and others. This approach possesses significant value; nevertheless, it does not yield spatial specified temperature distributions. (DAS 1984) used micro-hardness data to determine temperature distributions in high speed steel tools.

These readings were constrained in space by the indenter's dimensions and were instead temperature distributions averaged over time. Although (Boothroyd 1961) approximated tool and chip temperature distributions using infrared-sensitive film, the method's spatial and temporal precision were constrained by technical limitations. High spatial and temporal resolution measurements of machining have shown promise with modern, small, electronic photodetectors (Davies et al. 2003), although these measurements have exhibited differences with expectations. In an effort to circumvent the complexities of emissivity, these devices may be utilized as two- or three-color pyrometers (Müller et al. 2004; Al Huda et al. 2002). They are also capable of measuring the radiation released by the rake face.

Using an uncoated carbide and moderate cutting speeds, (Essel 2006) investigated the effects on flank wear, chip temperature, and cutting force during dry turning of AISI 1045 and other alloyed variants of AISI 1045 steels. (Denkena et al. 2007) established that alterations in cutting temperature, cutting forces, and chip formation resulted from a substantial increase in cutting speed under the high speed turning of AISI 1045 steel using a coated insert. (Davies, Cooke, and Larsen 2005) examined the distributions of temperature when cutting AISI 1045 steel for various cutting parameters; however, they neglected to account for cutting tool wear. (Qasim et al. 2015) optimized process settings for high speed machining of AISI 1045 steel. The researchers used various cutting tools to reduce cutting temperature and forces.

On the other hand, the cutting inserts' edge shape significantly affects process reactions, including cutting temperature, cutting forces, and surface roughness for cutting operations. Two common cutting-edge geometries are the classic round-nose and the more modern wiper. Achieving a satisfactory surface quality without further grinding is now possible with the help of the later, wiper inserts. The use of wiper inserts in machining may increase cutting force and temperature, which can be detrimental (Abbas et al. 2020). The impact of the wiper insert on the amount of metal removal, tool wear, cutting force, temperature, and surface integrity has been examined in several studies on machining performance (Rocha et al. 2017; A. Kumar, Pradhan, and Jain 2020). Although wiper inserts enhance metal removal rates and improve surface topography compared to conventional inserts (Zhang, Liu, and Guo 2017), they also increase cutting force and power consumption (Gaitonde et al. 2009). Additionally, it was discovered that using wiper inserts during machining causes the tool rake face to become hotter, leading to increased residual stresses and tool wear than when using conventional inserts (Jiang and Wang 2019). However, while it comes to tool wear, some prior research has shown that wiper inserts work better than conventional ones (Gaitonde et al. 2009). Furthermore, there was a lot of chip curling when wiper inserts were used, which means the chip separated from the tool rake face earlier (Zhang, Liu, and Guo 2017).

To decrease the cutting temperature of AISI 1045 steel for the turning operation, it is beneficial to comprehend the effects of altering the input process variables. The aim of this study was to determine the optimal combination of turning process parameters for AISI 1045 steel. Artificial Neural Networks are effective tools for engineering methods characterized by complex and nonlinear interactions between output and input parameters. ANNs have proven to be valuable in several engineering domains. Some examples of engineering challenges that ANNs have helped model, analyze, optimize, and predict include manufacturing (Khorasani and Yazdi 2017; Kant and Sangwan 2015; El-Bahloul 2020; Dabwan et al. 2025), welding (Sivagurumanikandan et al. 2018; Turkson et al. 2016), and 3D printing processes (Kaid et al. 2023; Shirmohammadi, Goushchi, and Keshtiban 2021; Giri et al. 2021). (R. Kumar et al. 2021) optimized Grey-Fuzzy Hybrid and Cascade Neural Network Modeling in the hard turning of AISI D2 steel to accomplish the optimum settings for cutting input variables concerning chip morphology, chip reduction coefficients, and flank wear. (Panda, Das, and Dhupal 2020) aimed to optimize tool wear, roughness, and cutting force when hard turning D3 steel with a mixed ceramic tool. (Panda, Ranjan Das, and Dhupal 2019) conducted an analysis of machining performance, developed mathematical models, executed multiple output response parametric optimization, and calculated the lifespan of the cutting tool while milling AISI 4340 hardened steel. (Senthilkumar, Sudha, and Muthukumar 2015) optimized the turning process and discovered a significant improvement in the required performance index using the Grey Fuzzy term. Since (Das et al. 2016) discovered a substantial improvement in grey fuzzy grade when related to grey relational grade, it was hoped that the optimization problem would be effectively addressed using the grey-fuzzy term.

Previous research indicated that the dry turning of AISI 1045 steel primarily affects cutting temperature, cutting forces, tool wear, surface quality, and chip formation. Investigations seldom indicate the application of improving these responses using artificial neural networks and various algorithms for temperature reduction. Therefore, the dry cutting method concerning cutting temperature needs further elaboration to satisfy surface quality in the machining field. Moreover, the use of a hybrid model combining artificial neural networks and evolutionary algorithms with the cutting parameters is hardly executed. Given the aforementioned reasons and to achieve the ideal configuration for reducing input parameters, a hybrid model integrating artificial neural networks and genetic algorithms has proven to be a more effective tool (Kaid et al. 2023); hence, it is employed in the present study to determine the optimal combination of input variables To further predict surface quality, a framework for quality part monitoring was also established to monitor and control the cutting temperature. In light of this, a detailed experimental examination and optimization are required. Figure 1 shows the conceptual outline for the present work.

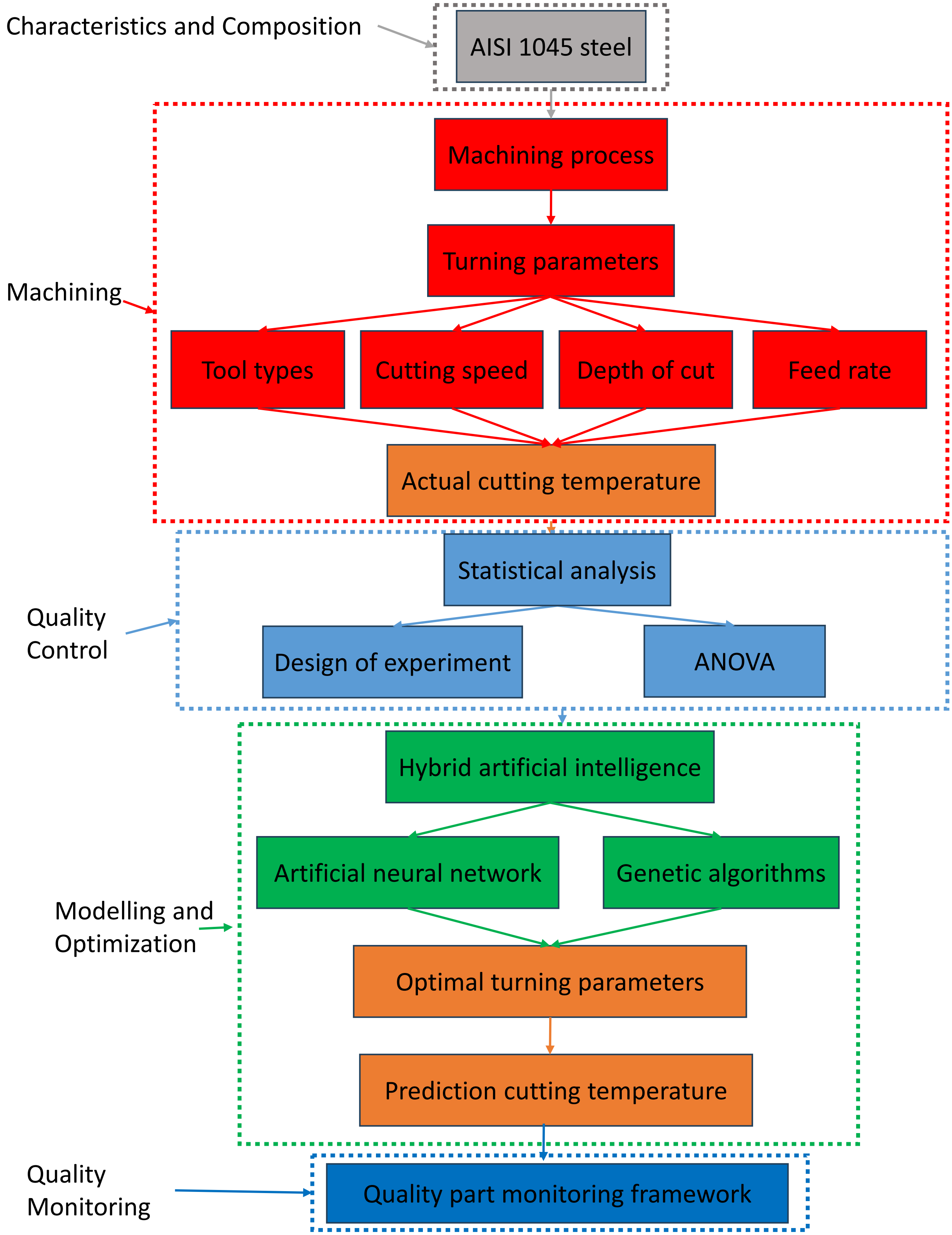

Figure 1. A structure for the present study

2. Materials and Methods

The cutting temperature obtained by turning AISI 1045 using a wiper and conventional carbide inserts was earlier documented by (Abbas, El Rayes, et al. 2023; Abbas, Al-Abduljabbar, et al. 2023). The present study employs data from (Abbas, El Rayes, et al. 2023; Abbas, Al-Abduljabbar, et al. 2023) as a substantial addition. This part begins by providing a concise summary of the treated material, containing its composition of chemical and mechanical characteristics. The machining setup, comprising the lathe, cutting tools, and characterization devices, is shown. The subsequent sector delineates the experimental design employed to execute the experiments. The hybrid model integrating artificial neural networks and genetic algorithms, together with their operational variables, is explained comprehensively.

2.1 Materials

This research utilizes AISI 1045 steel, often used in various industrial applications that need good wear resistance and strength. AISI 1045 exhibits excellent machinability throughout all machining processes, such as turning, drilling, milling, and broaching. The chemical composition of AISI 1045 steel alloy comprises Carbon (C) 0.45%, Phosphorus (P) 0.03%, Iron (Fe) 98.75%, Manganese (Mn) 0.65%, and Sulfur (S) 0.04% (Abbas, El Rayes, et al. 2023; Abbas, Al-Abduljabbar, et al. 2023). The mechanical qualities of AISI 1045 encompass an ultimate tensile strength of 565 MPa, a yield tensile strength of 310 MPa, an elongation at break (over 50 mm) of 16%, a reduction of area of 40%, a modulus of elasticity of 200 GPa, and a Vickers hardness of 170 (Abbas, El Rayes, et al. 2023; Abbas, Al-Abduljabbar, et al. 2023).

2.2 Machining setup

The parts were machined using a traditional lathe machine by Emco Company (Salzburg, Austria), the EMCOMAT-20D. The computerized speed controls allow the machine to reach speeds of up to 3000 rpm, and the drive motor is 5.3 kW. Between 0.045 and 0.787 mm/rev is the range of the longitudinal feed rate. The cutting tool is made by Sandvik (Stockholm, Sweden) and has a DCMT11 T304-PF 4315 conventional insert and a DCMX11 T304-WF 4315 wiper cutting insert. The holder is type SDJCR 2020K 11. For every set of trials, the cutting length was 30 mm, and the workpiece sample had dimensions of 70 mm in diameter and 120 mm in length.

2.3 Quality Evaluation

The quality of the components was assessed based on the measured cutting temperature. The minimal cutting temperature yields superior quality in component. Figure 2 shows the experimental work test rig, which includes cutting temperature measuring equipment and test component machining sets. The thermal pictures were captured using a thermographic camera of the ThermoPro-TP8 type, which was supplied by Guide (Wuhan, China). In order to evaluate temperatures, the camera must be focused on the target and the distance between them must be recorded. This data is then supplied to the analysis program. The surface between the cutting tool and the workpiece during the turning operation is the target of interest in this experiment, as illustrated in Figure 2.

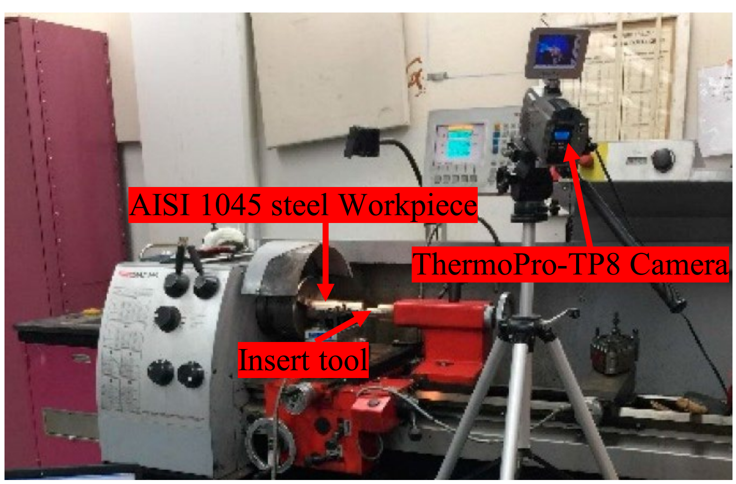

Figure 2. Experimental setup for machining test components and monitoring cutting temperature measurements (Abbas, El Rayes, et al. 2023)

There were 54 tests performed utilizing a full factorial design. The parameters included two levels of tool types (conventional and wiper carbide inserts) and three levels of depth of cut (0.5, 0.75, and 1.0 mm), feed rate (0.045, 0.09, and 0.135 mm/rev), and cutting speed (80, 120, and 160 m/min). The response is the cutting temperature (T) in degrees Celsius.

2.3 Hybrid Neural Network Algorithm with Genetic Algorithm

Artificial Neural Networks (ANN) constitute a prevalent model for calculating output based on various input parameters through hidden layers, as shown in Figure 3. Although artificial neural networks (ANNs) can monitor the intricate and nonlinear bond between independent input and output variables, they are hindered by restrictions, including poor learning rates. Thus, the utilization of optimization methods, particularly meta-heuristic algorithms, can significantly improve the efficiency of artificial neural networks (ANNs). Many academics presently use artificial neural networks with genetic algorithms (Cao et al. 2018; Azadeh et al. 2007; Li et al. 2003; Kaid et al. 2023; Dabwan et al. 2025) to identify optimal fitness values for one or multiple-target optimization challenges. This work employed ANN-GA hybrid algorithms to determine the optimum turning process variables for AISI 1045 steel concerning cutting temperature.

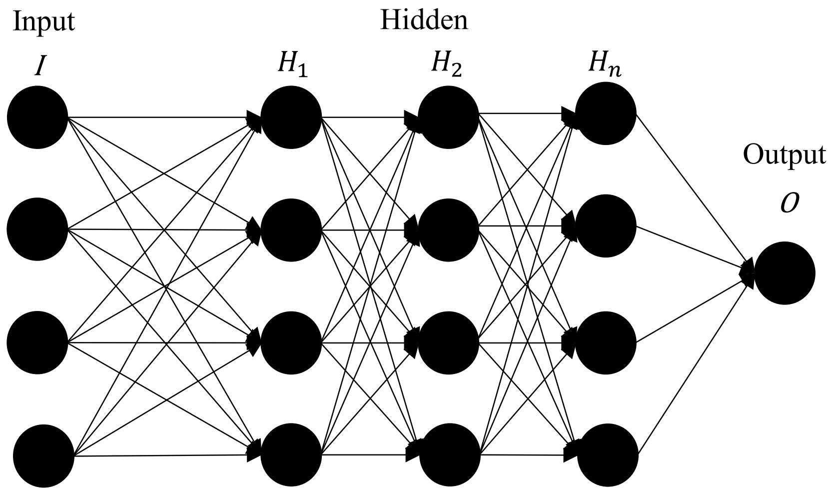

Figure 3. ANN structure

3. Results and Discussion

3.1 ANOVA analysis

Table 1 shows an ANOVA result for the cutting temperature after non-significant components were removed. The variables that significantly impact the output include tool types (T), depth of cut (d), feed rate (f), and cutting speed (S). The ANOVA Forward Selection technique was employed to eliminate non-significant variables, except for non-significant two-way interaction variables such as T and f, T and d and f and S, which could not be removed due to the presence of significant three-way interaction variables associated with these non-significant two-way interactions. Furthermore, as seen in Table 1, the variables T, f, d, and S substantially affected cutting temperature. The relationships between T and S, and d and S significantly impact the cutting temperature. The three-way interactions of T, f, and S, together with T, d, and S, significantly influence the cutting temperature. The adjusted R-squared value indicates that the model accounts for around 80.29% of the variability in the data. The disparity between the R-square and adjusted R-square values indicates that certain variables may not contribute much to explaining strength; yet the model remains robust overall. The predicted R-squared shows that 54.81% of the variance is from unidentified nuisance variables. Exploring neural networks or alternative machine learning methodologies may significantly improve the model's prediction performance.

Table 1. ANOVA results for minimum cutting temperature

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	29	23948.1	825.79	8.44	0.000
T	1	1515.0	1514.95	15.49	0.001
f	2	4851.4	2425.71	24.80	0.000
d	2	2006.3	1003.13	10.26	0.001
S	2	4700.8	2350.39	24.03	0.000
2-Way Interactions	14	8461.7	604.40	6.18	0.000
T*f	2	95.3	47.67	0.49	0.620
T*d	2	559.1	279.53	2.86	0.077
T*S	2	5995.5	2997.75	30.65	0.000
f*S	4	213.8	53.44	0.55	0.703
d*S	4	1598.0	399.50	4.09	0.012
3-Way Interactions	8	2413.0	301.62	3.08	0.015
T*f*S	4	1150.7	287.67	2.94	0.041
T*d*S	4	1262.3	315.57	3.23	0.030
R-sq = 91.07% R-sq (adj) = 80.29% R-sq (pred) = 54.81%					

3.2 Optimization of the ANN-GA model

This study presents a hybrid Artificial Neural Network (ANN) and Genetic Algorithm (GA) approach to optimize the turning process's input variables for AISI 1045 steel components, utilizing the software of MATLAB R2022b to minimize cutting temperature. The optimum outcomes were achieved with the ANN-GA (Ghasri 2023) MATLAB code. The artificial neural network has been trained to predict cutting temperature using 54 sets of process factors (tool type, cutting speed, depth of cut, and feed rate) and the corresponding output (cutting temperature). The significance of different variations and combinations is illustrated by subsequent findings, obtained through rigorous training and validation by artificial neural networks. Table 2 shows the ANN-GA model's goodness of fit, employed to assess the influence of transfer functions, network topology in the hidden and output layers, and the optimization method. The dependent variable's correlation coefficient, determination coefficient, and sum of squares errors can differ between topologies. Upon evaluating all potential permutations and combinations, the minimal root mean square error meets the requirements for choosing the optimal ANN-GA model. A reduced root-mean-squared error and a tightly correlated relative error allow for better prediction of the output variable. The Levenberg-Marquard training method and the ANN-GA approach were used for predicting the response values. Merging Tansig on the hidden layer with the Tansig transfer function on the output layer improves performance. Figure 4 displays the correlation between the actual and predicted values of cutting temperature by the ANN-GA.

Table 2. Experimental and predicted output by ANN-GA (experimental data was reported by (Abbas, El Rayes, et al. 2023)

No.	Experimental	Predicted	Relative Error
1	468.9	470.9943	0.004466
2	412.9	436.6897	0.057616
3	464.1	462.0137	0.004495
4	470.6	457.5325	0.027768
5	534.6	521.8665	0.023819
6	459.8	458.5879	0.002636

7	490.6	490.7451	0.000296
8	494.5	482.665	0.023933
9	449.6	458.0093	0.018704
10	462.8	457.5409	0.011364
11	460.3	467.9514	0.016623
12	464	461.6216	0.005126
13	462.6	457.7098	0.010571
14	475.5	469.6736	0.012253
15	465.8	470.987	0.011136
16	476.3	476.2325	0.000142
17	445.1	457.4842	0.027823
18	472.6	457.5962	0.031747
19	477.8	469.6242	0.017111
20	472.7	470.8456	0.003923
21	479.7	469.8277	0.02058
22	484.6	483.5911	0.002082
23	467	465.5567	0.003091
24	460.5	470.987	0.022773
25	450.7	447.9677	0.006062
26	464.1	470.9944	0.014855
27	472.1	471.4638	0.001348
28	473.2	470.9891	0.004672
29	485.12	486.0242	0.001864
30	477.9	470.9887	0.014462
31	462.1	464.3786	0.004931
32	471	471.7507	0.001594
33	461.9	470.7691	0.019201
34	512.7	515.2582	0.00499
35	462.8	465.2703	0.005338
36	487	469.5838	0.035762
37	457.2	457.4962	0.000648
38	474.8	470.9875	0.00803
39	554.4	556.8942	0.004499
40	511.1	509.4556	0.003217
41	472.7	470.9895	0.003619
42	462.6	470.0943	0.0162

43	469.9	468.4235	0.003142
44	493.7	489.3734	0.008764
45	476.2	482.665	0.013576
46	461	457.5348	0.007517
47	478.9	474.3954	0.009406
48	484.7	469.8591	0.030619
49	463.7	465.791	0.004509
50	474.2	468.4658	0.012092
51	419.3	455.589	0.086547
52	489.1	470.9684	0.037071
53	476.4	482.2558	0.012292
54	490	469.4853	0.041867

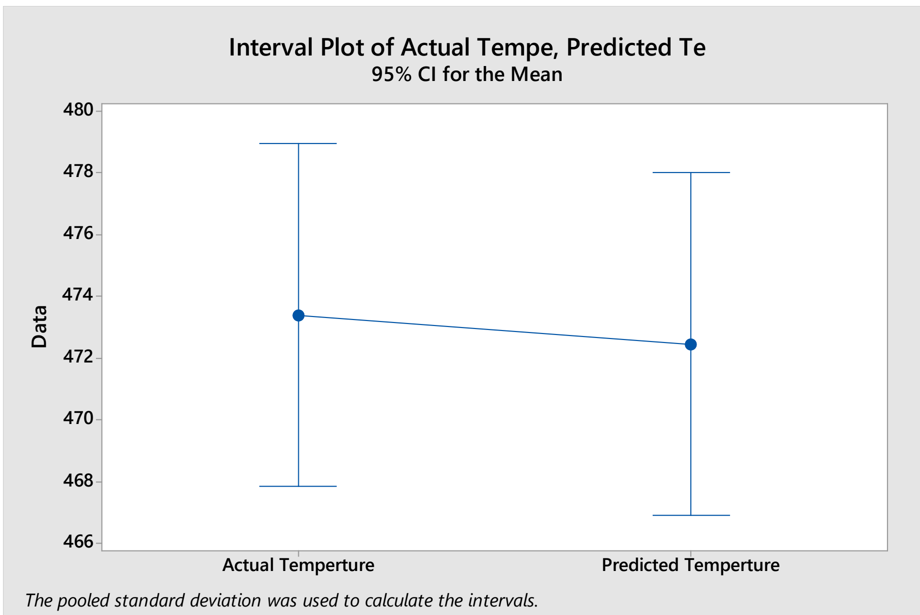

Figure 4. Comparing the actual and predicted temperature

Table 3 displays the t-test results that were performed for comparing the predicted and actual temperatures. This table shows several statistical measures, such as the T-value, p-value, standard deviation, mean, and standard error of the mean. According to the analysis of statistics performed for this work, the p-value for comparing the mean actual temperature with the mean predicted temperature is 0.81, as Table 3 illustrates. This p-value shows that there is no substantial difference between the actual and predicted temperature means. Therefore, the hybrid ANN-GA can predict optimal parameters based on the optimization outcomes.

Table 3. Two-sample t-test for actual and predicted temperature

	N	Mean	StDev	SE Mean	T-Value	P-Value
Actual Temperature	54	473.4	22.3	3.0	0.24	0.81
Predicted Temperature	54	472.5	18.8	2.6		

The optimal R-value of 0.90549 was found using the Levenberg-Marquardt method (refer to Figure 5). This method was quicker, but it consumed more memory. After eight iterations, the training data identifies the best solution as shown in Figure 6, and the epochs by default terminate when the MSE of the validating samples starts rising. At the eighth epoch, a validation performance of 205.241 was reached. An optimum parameter for a genetic algorithm (GA) would have the following settings: 300 iterations, 90 population size, 0.4 crossover %, 0.8 mutation percentage, and 6 hidden layers. After adjusting all of these settings to the lowest possible values, a conventional carbide insert type, depth of cut of 0.5 mm, feed rate of 0.045 mm/rev, and cutting speed of 80 m/min result in a minimum cutting temperature of 436.7 °C.

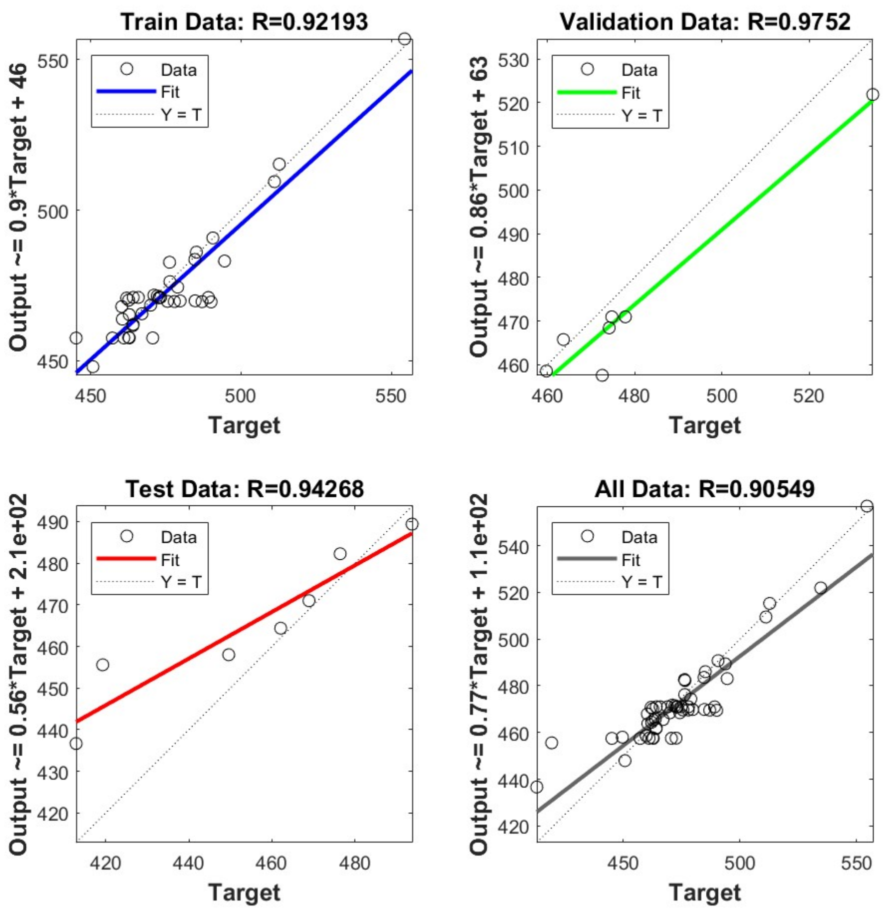

Figure 5. The ANN's regression plot

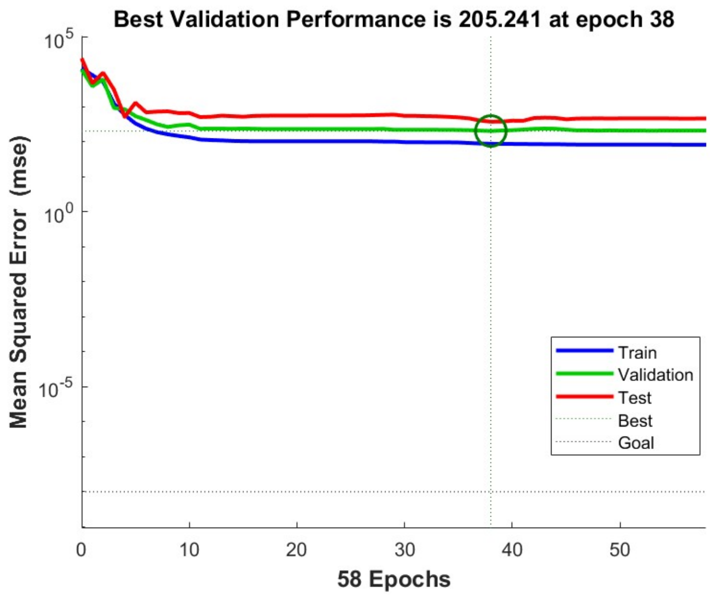

Figure 6. Plotting an ANN mean square error

Table 2 reveals that the largest relative error is 0.086, whilst the smallest is 0.000142. The comparison of these numbers indicates that there is no noticeable distinction between the actual and predicted values. In conclusion, the GA approach can be used in conjunction with the constructed neural network to significantly decrease cutting temperature. Evaluation and results from the neural network led us to the conclusion that the selected multilayer perceptron neural network is capable of predicting cutting temperature for components made of turned AISI 1045 steel. The experimental matrix indicates that employing a conventional carbide insert tool at a feed rate of 0.045 mm/rev, a cutting speed of 80 m/min, and a depth of cut of 0.5 mm results in the lowest cutting temperature of 412.9 °C, whereas optimization using the aforementioned ANN-GA parameters produces a cutting temperature of 436.7 °C.

3.3 Quality part monitoring framework

The Quality Part Monitoring Framework was developed to monitor and control the cutting temperature. This framework will be utilized to predict surface quality based on the current temperature and correlate it with the surface value stored in the database. A schematic depiction of the Quality Part Monitoring Framework is shown in Figure 7. The temperature of the cutting process is measured online during the turning process, and the signal is communicated to a computer for storing in a database. The temperature results are then compared to the stored data from the previous study mentioned by (Abbas, El Rayes, et al. 2023) that related to surface roughness. The low temperature is associated with good surface quality, whereas the high temperature is associated with bad surface quality, which suggests that there is a connection between the quality of the surface and the temperature of the cutting process. Throughout the machining process, the temperature of the cutting operation would be immediately monitored by this proposed framework, which would result in higher surface quality. High temperatures during the cutting process are associated with a poor surface quality, whereas low temperatures during the cutting process are associated with a higher surface quality. If a higher temperature is seen at any point throughout the process, the system will continually reset the parameters of the process until a lower temperature is reached, which will result in an improved surface quality of the part. This suggested framework would economically reduce the cost and time required for establishing surface quality measurement in the machining process post-operation.

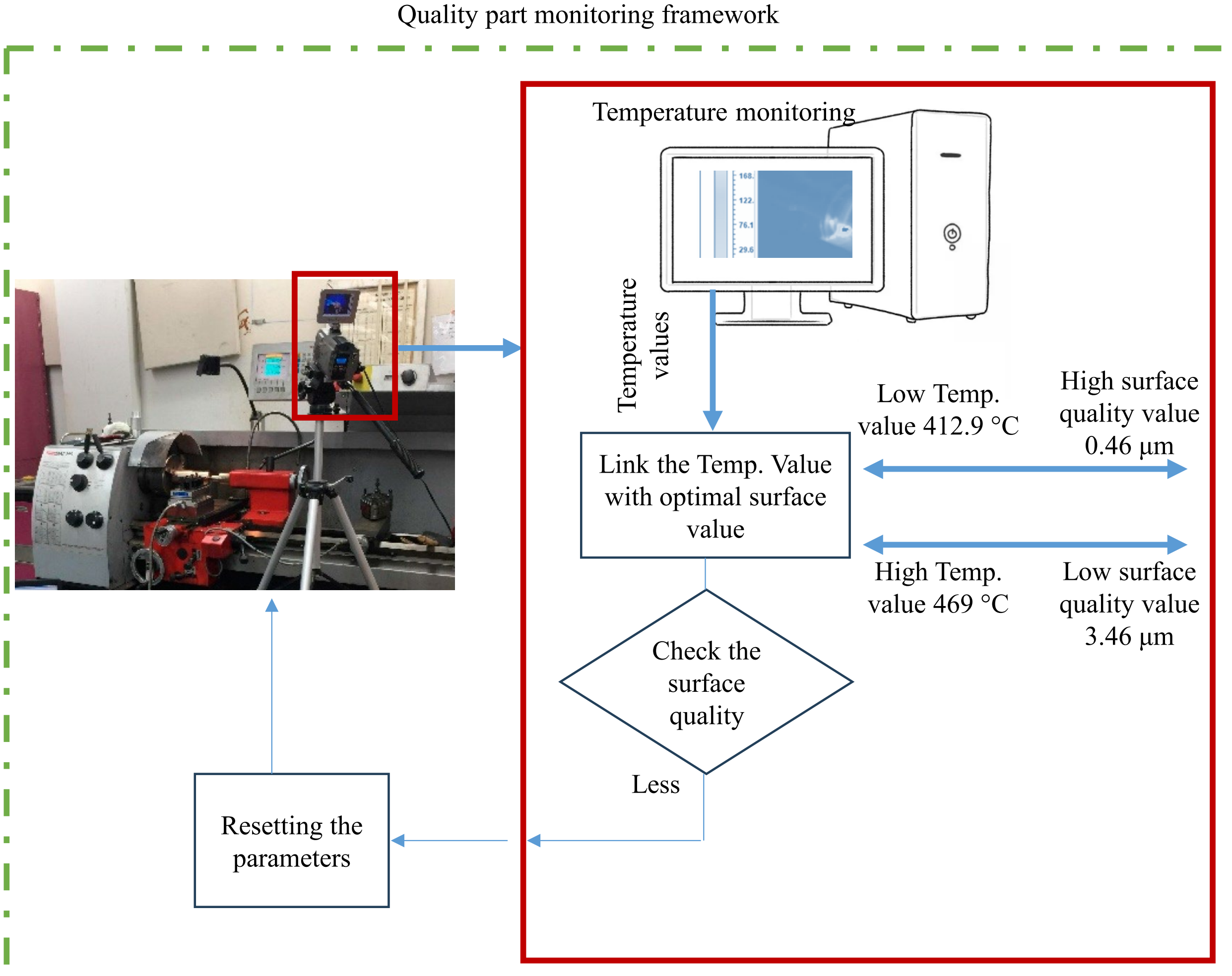

Figure 7. Framework for Monitoring Quality Components

4. Conclusion

Cutting temperature during dry turning of AISI 1045 steel is investigated in this article as a function of input process variables. The diversity of input factors was identified, and 54 experiments were then generated for this study. A full factorial design was conducted to investigate the cutting temperature of a turned AISI 1045 steel component. The influence of process variables, for example, tool type, feed rate, depth of cut, and cutting speed, was investigated. Furthermore, the AISI 1045 steel component's turning process parameters were enhanced using a hybrid approach utilizing an artificial neural network and a genetic algorithm (ANN-GA). In order to find the best combination of input parameters, genetic algorithms were used to combine the experiment matrix after training. The optimal parameter values have been empirically determined and evaluated in order to validate the models. According to the investigation, the process variables of feed rate, depth of cut, cutting speed, and tool type have an impact on the cutting temperature. A framework for Quality part monitoring was established to supervise and control cutting temperature in order to predict surface quality. During the studies, a conventional carbide insert tool was utilized to obtain a minimal cutting temperature of 412.9 °C to enhance the high surface quality of part. This was accomplished by maintaining a feed rate of 0.045 mm/rev, a depth of cut of 0.5 mm, and a cutting speed of 80 m/min. When using a hybrid ANN-GA tool with conventional carbide, a feed rate of 0.045 mm/rev, a cutting depth of 0.5 mm, and a cutting speed of 80 m/min, the resulting cutting temperature is 436.7 °C. Consequently, ANN-GA has improved the cutting temperature and is more efficient in achieving this outcome. Thus, for AISI 1045 steel, the efficacy of the turning process variables is improved by employing meta-heuristic algorithms.

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